Fertility Impacts of 3G Mobile Expansion: Evidence from Nigeria [*]

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Abstract

Diffusion theories of fertility transition have long emphasized the role of mass media technologies in spreading new ideas and norms, which in turn influence gender and demographic outcomes. The rapid expansion of the internet and mobile technologies creates novel channels for the diffusion of globalized norms and access to health and labor market resources, with the potential to shape fertility behaviors. Despite this theoretical potential, estimating the causal impacts of digital technology on fertility, especially in high-fertility contexts, has proven to be challenging because of the difficulty of disentangling selection into usage from true effects. Here, we construct a longitudinal panel by linking individual-level birth histories from the 2018 Nigeria Demographic and Health Survey (DHS) to annual mobile coverage maps to estimate the causal effect of mobile broadband (3G and beyond) expansion on fertility. We use a two-way fixed effects model, exploiting plausibly exogenous variation in the timing of 3G coverage rollout over time and space. We find that the expansion of 3G coverage during the study period led to a decline in fertility, corresponding to a 7% reduction in the annual probability of a woman having a birth.

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1 Introduction

The expansion of mobile broadband has brought about unprecedented change, reshaping economic development (Hjort and Poulsen, 2019; Aker and Mbiti, 2010; Hübler and Hartje, 2016; Blauw and Franses, 2016), culture (Smith, 2006; Tenhunen, 2008; Anstey Watkins et al., 2018), inequality (Garcia et al., 2018; Rotondi et al., 2020), and health care (Noordam et al., 2011; Zurovac et al., 2011). As these technologies evolve, they restructure markets and institutions while transforming social norms, relationships, and everyday behaviors. Today, billions of people access the internet primarily through mobile devices (GSMA, 2024; Breen et al., 2025), up from near-zero global penetration just two decades ago. These rapid technological shifts have the potential to reshape shape key demographic processes and outcomes. From the perspective of developmental idealism theory (Thornton, 2001), these new technologies act as powerful conduits of globalized norms about modernity, family, and reproduction. By expanding access to social media and communication, mobile broadband diffuses ideas about gender, fertility, and family that can accelerate demographic change.

The diffusion of mobile broadband may be especially consequential for fertility, affecting this demographic process through several potential pathways (Kashyap et al., 2023). Early 2G connectivity enabled voice and text communication, facilitating the spread of information and ideas within social networks. These social connectivity and interaction effects, central to diffusion theories of fertility (e.g., Montgomery and Casterline (1996)), are amplified with 3G internet, which broadens exposure to globalized norms and images, particularly through social media. Beyond information flows, mobile broadband expands access to financial, labor market, and health services via mobile money (Suri and Jack, 2016) and mobile health (mHealth) channels (Noordam et al., 2011). Internet-enabled phones also create new ways to meet partners, date, and engage in sexual interactions. Collectively, these highlight the multifaceted channels through which 3G internet expansion may shape fertility behavior. Despite this theoretical potential, empirical evidence on causal relationships remains limited due to the difficulty of distinguishing endogenous adoption of mobile technology from its true impacts on fertility.

In this study, we link birth history data from the 2018 Nigeria Demographic and Health Survey (DHS) with annual 3G mobile coverage maps from 2010–2018 to examine the relationship between 3G internet expansion and fertility. The DHS data are geo-referenced at the survey cluster level (the primary sampling units used in DHS surveys), allowing us to construct a longitudinal panel that links annual 3G coverage with women's birth histories. We use this panel to estimate two-way fixed effects (TWFE) models, leveraging plausibly exogenous variation in the timing of 3G rollout across clusters. This approach helps isolate the impact of 3G rollout by accounting for both time-invariant differences across clusters (e.g., geography, baseline fertility) and year-specific shocks (e.g., national policies or economic trends). We find that the introduction of full 3G coverage causes an approximate 7% decline in a woman's annual probability of having a birth over our observation window. We then examine channels through which 3G expansion influences fertility, finding suggestive evidence that it reduced ideal family size, increased contraceptive use, and increased women's autonomy over healthcare and financial decisions.

2 Background

2.1 Digital technology, development, and population processes

A growing body of literature has linked mobile technology expansion in both high and low- and middle-income countries (LMICs) with a number of development and population processes. Recent causal evidence suggests that mobile phone access increases household income and economic development (Hjort and Poulsen, 2019; Aker and Mbiti, 2010; Hübler and Hartje, 2016; Blauw and Franses, 2016), including in Nigeria (Bahia et al., 2024). Mobile phones have also been increasingly integrated into healthcare systems and service delivery (Noordam et al., 2011; Zurovac et al., 2011), including mHealth interventions, though the evidence of their effectiveness remains somewhat mixed (Marcolino et al., 2018). Flückiger and Ludwig (2023) investigate the causal impact of mobile phone coverage on infant mortality, estimating that infants are 0.9% less likely to die within the first year of birth when mobile coverage is available. Beyond these economic and health effects, the expansion of 3G internet reduces confidence in government, especially where traditional media are censored (Guriev, Melnikov and Zhuravskaya, 2021).

In contrast, far less attention has been paid to fertility outcomes. The strongest causal evidence evidence comes from a low-fertility, high-income context. In Germany, Billari, Giuntella and Stella (2019) exploited historical variation in telephone infrastructure that led to exogenous differences in broadband pricing, finding that broadband diffusion increased fertility. The effect was concentrated among higher-educated women, who were better able to reconcile work and family demands than their lower-educated peers, creating a "digital divide" in fertility.

Evidence from low- and middle-income settings points in the opposite direction. In a macro-level analysis looking at countries over time, Rotondi et al. (2020) find a consistent and positive association, particularly among countries at lower GDP per capita levels, between mobile phone diffusion and contraceptive adoption. In a complementary individual-level cross-sectional analysis focusing on seven African countries, they demonstrate higher levels of contraceptive knowledge and adoption among women who own mobile phones, a result robust to an instrumental variable strategy addressing the endogeneity of adoption (i.e., the possibility that ownership correlates with unobserved factors also shaping contraceptive use). Direct causal evidence on fertility is limited, but Billari, Rotondi and Trinitapoli (2020) uses longitudinal data from Malawi to show that women who own mobile phones have, on average, smaller family sizes and lower parity.

Together, these studies suggest a link between expansion of mobile technology and fertility. However, the available digital variables in the surveys cannot distinguish between types of technology (2G versus 3G) or measure technology use at the individual-level, and as a result, are limited in their ability to fully address the endogeneity of individual-level technology adoption.

2.2 Fertility in Nigeria

Nigeria is the most populous country in Africa, having nearly tripled its population over the past three decades. It is projected to double again in the next 35 years, surpassing the United States to become the world's third most populous country by 2050 (UN, 2025). This rapid growth is driven by high fertility: in 2018, the total fertility rate (TFR) was 5.3 children per woman (DHS, 2019), down only modestly from 6.0 in 1990. Age-specific fertility peaks at ages 25–29 (250 births per 1,000 women) but remains high—above 150 births per 1,000 women—into the early thirties.

Fertility is highly heterogeneous across social and regional lines. In 2018, the TFR was 6.7 among women with no education compared to 3.4 among those with more than secondary schooling (Olowolafe et al., 2023). Fertility is also higher in rural areas (5.9) than urban areas (4.5), and lowest in the South versus highest in the North, reflecting disparities in education and the country's sharp religious divide. Fertility preferences, as measured by ideal family size, remain high: on average, women want 6.1 children (DHS, 2019). Consistent with findings in other countries (Westoff, 2010), men report even higher desired fertility, averaging 7.2 children, more than one child above women's reported ideal.

2.3 3G expansion in Nigeria

Modern mobile network technology can be broadly divided into two eras: second generation (2G) and third generation (3G) and beyond.[1] The 2G era, beginning in the early 1990s, introduced digital signaling and encryption, replacing analog systems and enabling text messaging (SMS), basic data transmission, and improved call quality and security. In contrast, 3G networks, introduced in the early 2000s but rolled out later across much of the world, enabled fast data transfer rates and supported mobile internet access, video calls, social media, and multimedia streaming. Its adoption marked the start of widespread smartphone use, allowing for sophisticated mobile applications and modern internet browsing.

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[1] We use 3G as an umbrella term refer to 3G and more advanced mobile technologies, including 4G technology.

Our focus is on the impact of 3G coverage expansion, beyond 2G coverage, on fertility. Only 3G connectivity allows for access to online information and services, including health and family planning resources. It was also a key driver of exposure to social media (Rainie and Wellman, 2012), a channel through which the diffusion of ideas and global norms influences demographic outcomes such as fertility.

In the case of Nigeria, mobile phone coverage has expanded rapidly over the course of the past two decades (Forenbacher et al., 2019). As shown in Figure 1, only 18% of individuals lived in areas with 3G coverage in 2010, while approximately 62% of individuals lived in areas with 3G coverage in 2018. This rapid yet staggered rollout of 3G across time and place in Nigeria provides a unique opportunity to identify its impact on fertility outcomes.

Figure 1 about here.

2.4 Mechanisms linking 3G expansion and fertility

There are several theoretical reasons to expect 3G expansion to affect fertility. As illustrated in Figure 2, we classify these mechanisms into changes in ideation, autonomy, and demographic behavior. We briefly review these mechanisms below.

Figure 2 about here.

2.4.1 Ideation Channels

Demographers have long argued for the importance of diffusion theories in explaining fertility behavior (Montgomery and Casterline, 1996; Casterline, 2001). These theories emphasize the roles of social learning (acquiring knowledge by observing others' behavior) and social influence (modifying behavior in response to others' beliefs or actions) in shaping fertility outcomes. Intentions to have children, as well as the social aspects surrounding fertility, are influenced by social interactions with others (Rossier and Bernardi, 2009).

The internet and social media have transformed how people interact and learn, reshaping diffusion processes around fertility. The expansion of 3G internet broadened access to diverse cultural norms and ideas about childbearing, particularly through social media. This exposure can include modern perspectives on contraception, ideal family size, and delayed childbearing (Ning et al., 2022), as well as backlashes to these ideas. Social media enables both passive consumption and active engagement with such content across regions and national borders, fostering exchanges of values and practices related to fertility. Empirical evidence supports these dynamics: Facebook use is strongly associated with lower birth rates (Wildeman, Schrijner and Smits, 2023), and social media platforms can provide forms of social support that influence fertility outcomes (Miller et al., 2022).

A related ideational mechanism through which 3G expansion may affect fertility is its influence on contraception. Mobile internet can improve knowledge of and shift demand for modern methods. This distinction matters because uptake generally lags behind supply: barriers to adoption are driven less by availability than by preferences and norms (Senderowicz and Maloney, 2022). Expanded mobile internet can expose women to reproductive health and family planning information, increasing awareness and shaping preferences for modern contraceptive methods that lower fertility (Rotondi et al., 2020).

2.4.2 Autonomy Channels

Expanded 3G coverage and access to mobile phones generally creates improved economic conditions (Hübler and Hartje, 2016; Blauw and Franses, 2016), and there is a longstanding negative relationship between economic development and fertility in high-fertility contexts (Lesthaeghe, 2010), although there are some exceptions in high-income, low-fertility contexts (Fox, Klüsener and Myrskylä, 2019). In Nigeria, 3G coverage reduced poverty and bolstered labor force participation, especially among poorer households (Bahia et al., 2024). Improved economic conditions may also create more opportunities for women to join the labor market, which is generally associated with declining fertility (Behrman and Gonalons-Pons, 2020).

Access to 3G internet can also shift intra-household dynamics and increase women's autonomy. Mobile phone ownership is positively associated with greater decision-making power among women, and with lower acceptance of intimate partner violence among men (Pesando, 2022). Increases in mobile access have also been linked to improvements in multiple dimensions of empowerment, including mobility, financial control, and exposure to health messaging. Empowerment, in turn, is generally associated with lower fertility intentions, greater contraceptive use, and longer birth intervals (Upadhyay et al., 2014). Lower fertility is linked to higher women's autonomy; higher women's autonomy increases the number of activities women can engage in and the value of women's time, making the decision to have children more costly (Sen, 1999; Dyson and Moore, 1983). Together, these findings suggest that expanded mobile internet may shift fertility behavior not only through information access, but also through changes in gender norms and bargaining power within families. This autonomy is especially salient in Nigeria, where men report larger ideal family sizes than women (7.2 vs. 6.1 ideal family size).

2.4.3 Demographic channels

There is also potential for 3G expansion to affect demographic behaviors upstream of fertility. The internet is increasingly central to relationship formation (Sironi and Kashyap, 2022; Sautter, Tippett and Morgan, 2010), including in Nigeria (Bolaji and Olatunji, 2018; Dunu, 2022). Mobile broadband may change the frequency of sexual encounters and the age at which women become sexually active. It is a priori unclear whether expanded 3G access in Nigeria increases or reduces relationship formation. How shifts in the timing and dynamics of these relationships ultimately shape fertility outcomes also remains uncertain.

Another potential channel is child mortality. The expansion of mobile internet may contribute to lower child mortality by improving access to health information and services, though direct evidence for Nigeria is lacking. For instance, Flückiger and Ludwig (2023) find that mobile internet expansion is associated with roughly a 1% decline in infant mortality across countries. Such declines may influence fertility because improved child survival reduces the need for additional births to achieve desired family size. By lowering the risk of infant and child death, mobile internet may shift parental decision-making toward smaller families, contributing to fertility decline.

3 Data and Methods

We construct a longitudinal panel by linking individual-level birth histories from the Nigeria 2018 DHS to annual mobile coverage maps in Nigeria. Our panel is restricted to the years of 2010-2018, the years where both retrospective fertility history and 3G coverage maps are available. Below, we describe the survey data and the mobile coverage maps in detail.

3.1 Individual-level survey data

The individual-level data are drawn from the 2018 Nigeria DHS. The sampling frame for the survey is based on the 2006 Population and Housing Census of the Federal Republic of Nigeria (NPHC). The sample is selected using a stratified, two-stage cluster design within primary sampling units ("clusters"), which usually correspond to the census enumeration areas. Each cluster contains approximately 100-300 households; each household in the cluster is enumerated and a random set of households are selected. The selected households are visited by a trained survey enumerator who administers the full DHS survey instrument. Each DHS cluster is geo-referenced using GPS, with random displacement applied to preserve privacy: up to 2 km in urban areas, 5 km in rural areas, and up to 10 km for 1% of rural clusters.

This survey samples women aged 15–49 (N = 41,623) and collects complete retrospective birth histories, including the month and year of each birth and the survival status of each child. The large sample of women of childbearing age provides sufficient power to quantify fertility differences across subgroups and to identify potential impacts of 3G expansion. Although the DHS is not longitudinal, the retrospective birth histories allow us to assess whether an individual woman had a live birth in a given year, facilitating the linkage to mobile coverage data.

3.2 Linkage with mobile coverage maps

We use annual 2G and 3G mobile coverage maps for Nigeria obtained from GSMA, the global association of mobile network operators, covering 2010–2019. These maps come from GSMA's Connectivity Maps programme, and provide more detailed spatial and temporal resolution, with better operator coverage across major operators, than other mobile coverage map products, such as GSMA Collins Bartholomews Mobile Coverage Explorer or the more community-driven open-data database of OpenCellID. Further technical details on processing the coverage maps as well as our assessment of their reliability for modelling 3G rollout are discussed in Appendix A.

To process the coverage maps, we first construct buffers around the displaced coordinates of each DHS cluster. These buffers are 2km for urban areas or 10km for rural areas, corresponding to the maximum amount of displacement. We then overlay these buffers with 2G and 3G coverage maps and 100m X 100m UN-adjusted population counts from Worldpop (WorldPop, 2023) and calculate the proportion of people living in each cluster covered by a 2G and 3G network.

3.3 Identification strategy

3.3.1 Theoretical Estimand

The primary inferential goal of this study is to estimate the causal effect of 3G expansion on fertility. We first define a theoretical estimand, the precise quantity we are interested in estimating (Lundberg, Johnson and Stewart, 2021). The theoretical estimand is composed of two key building blocks: a *unit specific quantity* and a *target population*. The *unit specific quantity* is a quantity defined for each unit of the population. In our analysis, the *unit specific quantity* is the counterfactual difference in the probability that a woman had a birth in the past year if she lived in a cluster with 3G mobile coverage versus without it. The *target population*, the set of units over which the *unit specific quantity* is aggregated, is all women living in Nigeria between the ages of 15 and 49.

Using the potential outcome framework (Imbens and Rubin, 2015), we can define our theoretical estimand (Ψ) as an average treatment effect (ATE):

$$\Psi_{\text{ATE}} = \underbrace{\underbrace{\frac{1}{n}\sum_{i=1}^{n}}_{\substack{\text{Mean over every } i \text{ among}\\ \text{childbearing-age women}}}}_{\text{Target Population}} \underbrace{\left(\underbrace{B_i(\textit{3G coverage})}_{\substack{\text{Probability of birth}\\ \text{if 3G coverage}}} - \underbrace{B_i(\textit{No 3g Coverage})}_{\substack{\text{Probability of birth}\\ \text{if no 3G coverage}}} \right)}_{\text{Unit-Specific Quantity}} \tag{1}$$

3.3.2 Empirical Estimand

The theoretical estimand Ψ is by definition impossible to estimate based on our observed data alone, as for each woman we can only observe one of the two potential outcomes. We therefore define an *empirical estimand* that can be estimated based on our observed data. Specifically, we estimate a two-way fixed effects (TWFE) linear probability model in which the outcome is a binary indicator for whether a woman had a birth in the past year. The key independent variable is the lagged proportion of a population covered by 3G mobile signal in a given year. Our model takes the form:

$$B_{ict} = \beta_0 \quad + \quad \underbrace{\beta_1 3\mathrm{G}_{ct} + \beta_1 2\mathrm{G}_{ct}}_{\text{3G and 2G coverage intensity}} \quad + \underbrace{\gamma_c}_{\text{Cluster FE}} \quad + \underbrace{\delta_t}_{\text{Year FE}} \quad + \underbrace{\boldsymbol{\beta}\mathbf{X}i}_{\text{Controls}} \quad + \epsilon_{ict} \qquad (2)$$

where B_{ict} is an indicator for whether woman i in cluster c at time t had a birth in the past year, $3\mathrm{G}_{ct}$ is the proportion of the population in the buffer around cluster i with 3G coverage in year $t-1$, $2\mathrm{G}_{ct}$ is the proportion of the population in the buffer around cluster i with 2G coverage in year $t-1$, γ_c and δ_t are cluster and year fixed effects, and $\mathbf{X}_i$ is a vector of control variables. In the fully specified model, $\mathbf{X}_i$ includes individual-level sociodemographic and behavioral factors (household wealth, urban/rural residence, age, employment status, education, religion, television and radio use), fertility-related measures (baseline parity and an interaction between year and an indicator for having had a birth in 2010–2011 at the beginning of our window),[2] and time-varying cluster-level covariates (GDP, temperature, rainfall, nightlights).

This TWFE model exploits variation in 3G mobile coverage across clusters and over time, comparing changes in birth rates between clusters with greater 3G expansion and those with less, from 2010 to 2018. The key identifying assumption is that 3G rollout is plausibly exogenous to fertility trends within clusters, driven by technical and business factors rather

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[2] Including this interaction allows fertility trajectories to differ for women who entered the panel with a birth in the years preceding lagged treatment versus those who did not. Because recent fertility strongly predicts subsequent childbearing dynamics, this specification helps control for heterogeneity in baseline fertility timing that could otherwise bias estimates of the impact of 3G expansion.

than fertility itself (Flückiger and Ludwig, 2023; Bahia et al., 2024). By leveraging within-cluster changes and controlling for year fixed effects, the model isolates the association between 3G coverage intensity and birth rates, net of time-invariant cluster characteristics and common shocks.

We focus on clusters without 3G coverage in 2010 to avoid conflating early-adopter areas with later rollouts. This restriction strengthens causal interpretation by ensuring all clusters begin from a common baseline of zero coverage.

4 Results

4.1 Unadjusted differences in fertility

We first present differences in unadjusted fertility rates. Figure 3 shows the total fertility rate (TFR), the average number of children a woman would have if she experienced the period's age-specific fertility rates throughout her reproductive life, in 2018 for women living in clusters with high 3G coverage (90%+ population coverage), further stratified by mobile phone ownership.[3] Women in clusters with 3G coverage who own a mobile phone have the lowest TFR of 4.00, while those in clusters without 3G coverage but with a mobile phone have a TFR of 5.04. The highest TFR of 6.68 is observed among women without a mobile phone in clusters with low 3G coverage.

Figure 3 about here.

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[3] For estimation, we use the conventional three-year, retrospective window used by the DHS program. We calculate the TFR using individual and cluster weights and the jackknife method for estimating standard errors (Croft, Courtney and Blake, 2023).

4.2 Causal impact of 3G expansion

Next, we present results from our TWFE model described in Equation 3. The baseline model includes fixed effects for cluster, year, and parity controls. This effect is modestly attenuated after adjusting for cluster-specific, time-varying controls for nightlights, GDP, rainfall and temperature. While the baseline cluster fixed effects absorb time-invariant heterogeneity, the cluster-specific time-varying controls account for contemporaneous local shocks that could otherwise bias the estimated effect of 3G expansion.

As shown in Figure 4, our baseline model shows that full treatment (expansion from 0% to 100% of population coverage) causes a reduction in births of approximately 1.5% per year. Evaluated at population baseline of 17% of women having birth in a given year, this represents a 7% reduction in the probability of having a birth in the past year.

We also fit a model with mother fixed effects, which exploits only within-mother variation across periods and thereby controls for all time-invariant maternal characteristics. The results are highly consistent with our TWFE estimates. For the full set of regressions coefficients, see Table A1.[4]

We replicate our results in two complementary analyses. First, because treatment is staggered over time, we re-estimate effects using the estimator proposed by Sun and Abraham (2021), which corrects for potential bias in TWFE models with heterogeneous treatment timing. The results are highly consistent with our main specification (see Appendix B), suggesting that our findings are not driven by differential pretrends and are not sensitive to estimator choice. Second, we use the 2008 Nigeria DHS and implement a pseudo-cluster

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[4] A model without year and cluster fixed effects gives inflated estimates of the negative association 3G–fertility association, demonstrating the importance of controlling for temporal and spatial confounding.

design. As the DHS surveys are cross-sectional and rely on different clusters in each wave, we match each 2018 cluster to the geographically closest cluster in 2008 to construct a pseudo-panel. We then compare changes in births over the past five years across these pseudo clusters and estimate a 4–8% decline in fertility attributable to 3G expansion.

Figure 4 about here.

4.3 Effect Heterogeneity

To what extent does the magnitude and direction of effects vary across population subgroups? First, we test heterogeneity by baseline levels of development, proxied by nightlight intensity in 2018. As shown in Figure 5, effects are largest in low-development areas. We fit a model with an interaction between 3G coverage and nightlight tertiles (low, medium, high).

Second, we test whether effects are larger among women who owned a mobile phone in 2018, when phone ownership was observed. This measure is imperfect, as some women who reported ownership in 2018 may have acquired a phone only recently, while some non-owners may have had access in the past, but it provides a useful proxy for exposure. We find substantially larger effects among women who owned mobile phones, and no significant effect among those who did not.

Third, we examine heterogeneity by marital status, distinguishing between monogamous and polygynous unions. A substantial share of women are in polygynous unions, where husbands have multiple wives. We classify women as unmarried, monogamously married, or polygynously married. We find no effect among unmarried women, likely reflecting limited statistical power given their much lower birth rates, and no effect among women in polygynous unions. By contrast, we observe a large negative effect among women in monogamous unions (Figure A7). Finally, we find no evidence of substantial regional differences between the North and South (Figure A8).

Figure 5 about here.

4.4 Evidence on mechanisms

Next, we examine the potential mechanisms reviewed in Section 2.4. Unlike our main outcome of having a birth in a given year, these outcomes, with the exception of infant mortality, are observed only cross-sectionally in 2018. This limits our ability to test them in a causal framework. To explore their potential role, we look at the association between the increase in 3G coverage between 2010 and 2018 and reported 2018 DHS outcomes, controlling for individual characteristics and a set of cluster-level controls measured in 2010 (rainfall, nightlights, road access, and infant mortality rate). This evidence is suggestive and associative in nature, rather than causal.

As shown in Figure 6, we find no evidence of a relationship between 3G expansion and age of first cohabitation nor age of first sexual intercourse. We observe a larger association for ideal family size, with 3G coverage being associated with an ideal family size of approximately 0.33 fewer children. Ideal family size is measured using the following question: "If you could choose exactly the number of children to have in your whole life, how many would that be?" We find no significant association between 3G expansion and women's labor force participation. These associations suggests that 3G rollout has no meaningful impact on timing of sexual relationship, but does shift desired fertility.

Figure 6 about here.

Next, we investigate whether 3G expansion has any impact on contraception use. As shown in Figure 7, we find evidence that 3G expansion is associated with an increase in adoption of modern contraception methods. This association is strong and significant for older, but not younger, women, who may have already achieved their desired fertility. There is no association between "folkloric" contraception methods (charms, herbal remedies) or traditional contraception (calendar method, abstinence) and 3G expansion. There is an increase in contraceptive knowledge across all age groups, but knowledge of modern methods was already high in 2018: 98% awareness among sexually active unmarried women and 94% awareness among currently married women (Program, 2023).

Figure 7 about here.

Empowerment and autonomy is another potential mechanism through which the expansion of 3G internet can affect fertility. We investigate a series of empowerment-related questions in the DHS. Responses are coded as woman deciding alone, joint decision with husband, or husband decides alone. While both autonomous and joint decision-making can reflect empowerment, we disaggregate to distinguish between them. In Figure 8, we find consistently small and statistically insignificant associations for joint decision-making. However, we find a positive association between 3G expansion and women autonomously making decisions around spending their own earnings and healthcare decisions. This suggests that one plausible mechanism linking 3G expansion to fertility decline is increased empowerment over health and contraceptive decision-making.

Figure 8 about here.

Finally, we examine whether declines in infant mortality could account for the fertility effects of 3G expansion. If 3G expansion reduces infant mortality, women may require fewer births to achieve their desired family size. Alternatively, lower community-level infant mortality rates may increase women's desire in having another child. To test this mechanism, we estimate a TWFE model similar to our main specification with fertility, except the outcome is the probability of a child dying in the first year of life. The results show no statistically significant impact of 3G expansion on infant mortality (Figure A5), suggesting that this pathway does not explain the observed fertility decline.

5 Discussion

Using linked birth histories and longitudinal 3G coverage rollout maps, we find a significant negative effect of 3G expansion on fertility. Descriptively, fertility rates are lower in clusters with high 3G coverage, but this more reflects selection into covered areas rather than the causal effect of 3G internet. To address this endogeneity—the possibility that unobserved factors correlated with both 3G coverage and fertility behavior may bias our estimates—we employ a two-way fixed effect model. This method leverages temporal and spatial variation in 3G rollout to identify the causal effect of expanding 3G coverage on fertility. We estimate a 7% reduction in the probability of having a birth in a given year on average over our observation window of 2010–2018. We replicate our main findings using both the Sun and Abraham estimator (Sun and Abraham, 2021), which corrects for potential bias in staggered TWFE designs, and a pseudo-cluster panel linking 2008 and 2018 DHS waves, with both approaches confirming our observed decline in fertility from 3G expansion. In particular the lack of pre-trends shows that fertility outcomes in areas that later received 3G were evolving similarly to those that had not yet received it, before rollout.

Our observed effect size is substantial, but comparable to those observed for other interventions known to influence fertility. In Kenya, educational subsidies reduced unwanted pregnancy among adolescents from 13% to 10% (Duflo, Dupas and Kremer, 2015). In Matlab, Bangladesh, maternal and child health and family planning programs caused fertility declines of 17% (Joshi and Schultz, 2012), and in India, the expansion of cable television led to a reduction of 0.5–0.8 children per woman (Jensen and Oster, 2009). In Brazil, direct exposure to a popular soap opera portraying small families as a desirable norm reduced fertility, particularly among lower-income women by about 7% (La Ferrara, Chong and Duryea, 2012).Our estimates are of a similar magnitude, suggesting that mobile broadband is a driver of fertility change rivaling other major social and policy interventions.

We find that the effects are heterogeneous across levels of development (proxied by nightlight intensity in 2018), with larger reductions in fertility in less developed clusters. There are a few plausible implications of this. First, digital connectivity may serve as a substitute for traditional information and service gaps in low-development settings, amplifying its behavioral effects. More developed areas may have already been exposed to modern ideals surrounding family size. Second, fertility responses may be more elastic in high-fertility areas where baseline access to education, employment opportunities, or reproductive health services is limited. Finally, this highlights the potential for digital infrastructure to most rapidly speed up the demographic transition among those with highest fertility.

The effect is primarily concentrated among women who owned mobile phones at the end of our observation window.[5] This points to the importance of individual access to mobile technology in mediating the fertility effects of digital expansion. Women with phones are better positioned to exploit new information flows and be exposed to globalized norms, while those without phones may not have direct exposure. This suggests that the demographic effects of digital infrastructure depend not only on geographic rollout but also on patterns of individual technology adoption. Further, The absence of effects among non-owners suggests that fertility impacts operate primarily through individual phone access rather than household or community spillovers.

Our analysis of potential mechanisms suggests that the fertility-reducing effect of 3G expansion operates through several channels. Most notably, 3G rollout is associated with declines in ideal family size, consistent with ideational change that reduces demand for children. This aligns with the theory that mobile broadband exposes women in high-fertility contexts to globalized norms that shift fertility preferences toward smaller families.

We found mixed support for potential demographic channels. We find no evidence that 3G expansion delayed sexual initiation or age at first cohabitation. We do, however, find an increase in the already very high knowledge of modern contraception and an uptake in modern, but not traditional or folkloric, contraception. This suggests that mobile internet

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[5] We cannot observe longitudinal patterns of phone ownership over our window, making it difficult to disentangle whether access preceded 3G expansion or was itself shaped by it. Nonetheless, phone ownership in 2018 provides a useful lower-bound proxy for exposure: women without phones are unlikely to directly benefit from expanded coverage, whereas effects among owners may vary with the timing of adoption.

increases access to accurate contraceptive information. Somewhat surprisingly given past findings (Hjort and Poulsen, 2019; Bahia et al., 2024), we find no significant association with increased female labor force participation. This may reflect that fertility decisions adjust faster than labor supply, that entrenched gender norms continue to constrain women's employment opportunities, or measurement error: the DHS labor force question may not pick up digital micro-entrepreneurship or other employment driven by new opportunities offered by mobile broadband.

Finally, we find evidence of women's autonomy in financial and healthcare decision-making. Autonomy is conceptually challenging, and hard to capture within the limitations of a standard household survey. Nonetheless, we find 3G expansion is associated with women being significantly more likely to make decisions autonomously without their husband about their health and how they spend their earnings. This is especially salient given that Nigerian women, on average, desire approximately one child fewer than men. We do not find significant changes in women's autonomy for making large household purchases, spending husband's earnings, nor making visits to family.

Together, these results provide theoretical support for our main findings. While not strictly causal, they offer suggestive evidence that fertility decline is driven by downward shifts in fertility preferences toward smaller families, greater contraceptive knowledge, and increased women's empowerment.

There are several limitations and avenues for future research. With the exception of mobile coverage and fertility and mortality outcomes from retrospective birth histories, our individual-level control variables in our main TWFE models are observed cross-sectionally in 2018. Many of these covariates are likely stable over time over our window (e.g., religion), and the inclusion of these potential post-treatment controls do not change our estimates (Table A1). Future work could also explore and quantify the relative contributions of different mechanisms in a more rigorous framework. In particular, figuring out specifically how 3G exposure changes change in fertility desires is a promising avenue for future research.

Nigeria is a valuable case study because it has reliable longitudinal data on 3G coverage and rollout. Yet the speed and intensity of Nigeria's 3G expansion is not unique: many countries experienced rapid adoption during this period, and many more will do so in the coming decade (Breen et al., 2025; Fatehkia, Kashyap and Weber, 2018). Whether our findings extend to other countries remains an open empirical question. Addressing it will require greater investment in data infrastructure to track the expansion of digital technologies and adoption patterns over time. Our findings demonstrate that digital infrastructure can accelerate demographic transitions by reshaping fertility preferences and behaviors. As mobile broadband continues to expand rapidly across high-fertility regions, understanding these demographic effects will continue to be essential for both demographic theory and policy aimed at managing population change and development.

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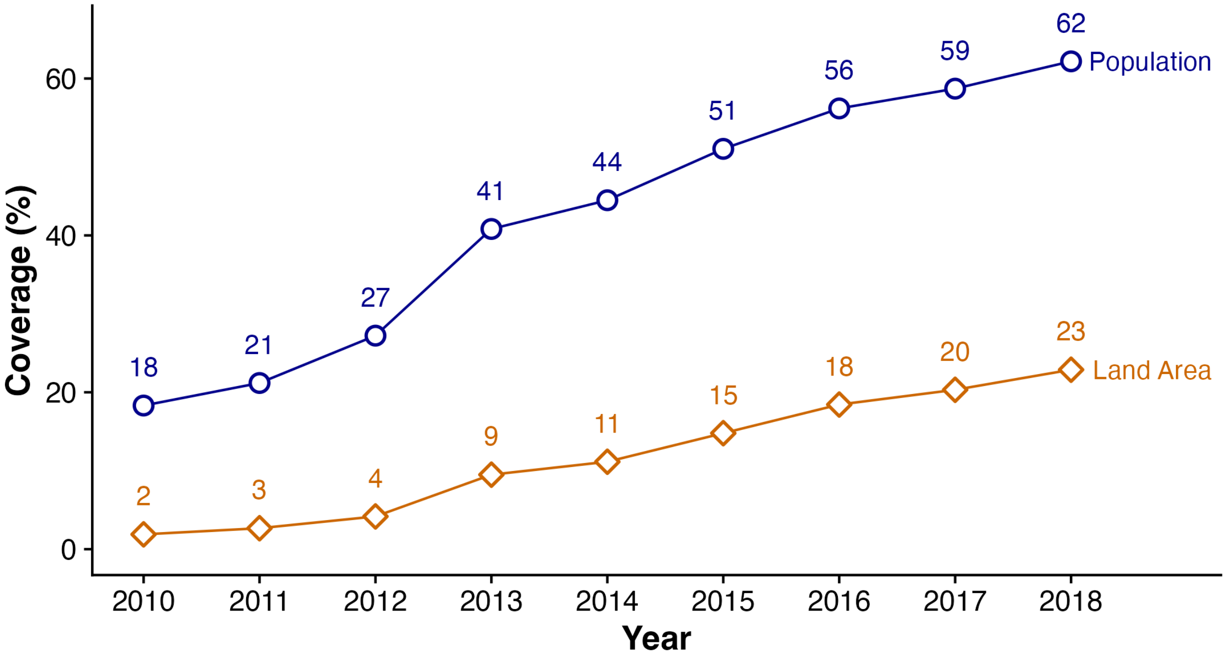

Figure 1: Expansion of 3G coverage across Nigeria over the study period. Coverage estimates are based on GSMA mobile coverage maps; population estimates are from WorldPop. Population line (purple) represents the total proportion of the population with 3G coverage. Land area (orange) represents the total proportion of national territory with 3G coverage.

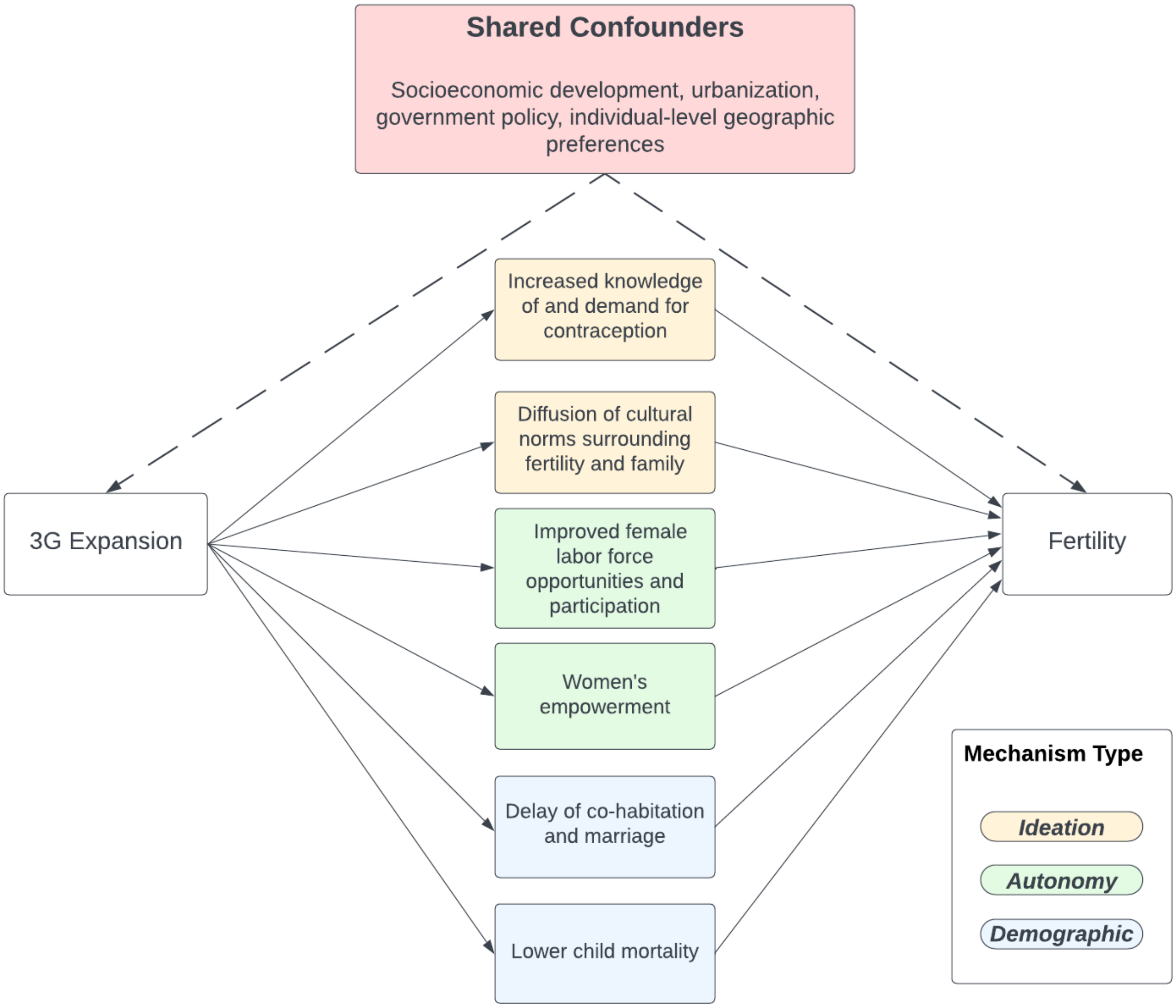

Figure 2: Theoretical mechanisms connecting 3G internet expansion with fertility.

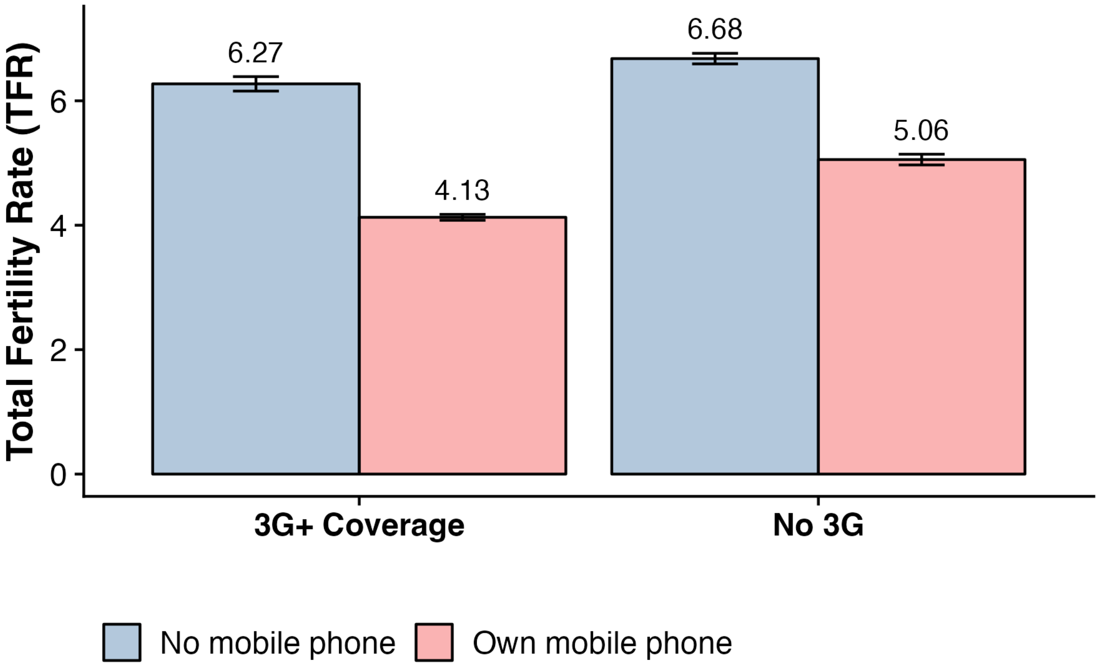

Figure 3: The unadjusted total fertility rate (TFR) stratified by mobile phone ownership and 3G coverage in 2018. The TFR is the average number of children a woman would have over her lifetime if she experienced current age-specific fertility rates throughout her reproductive years. Error bars show 95% confidence intervals.

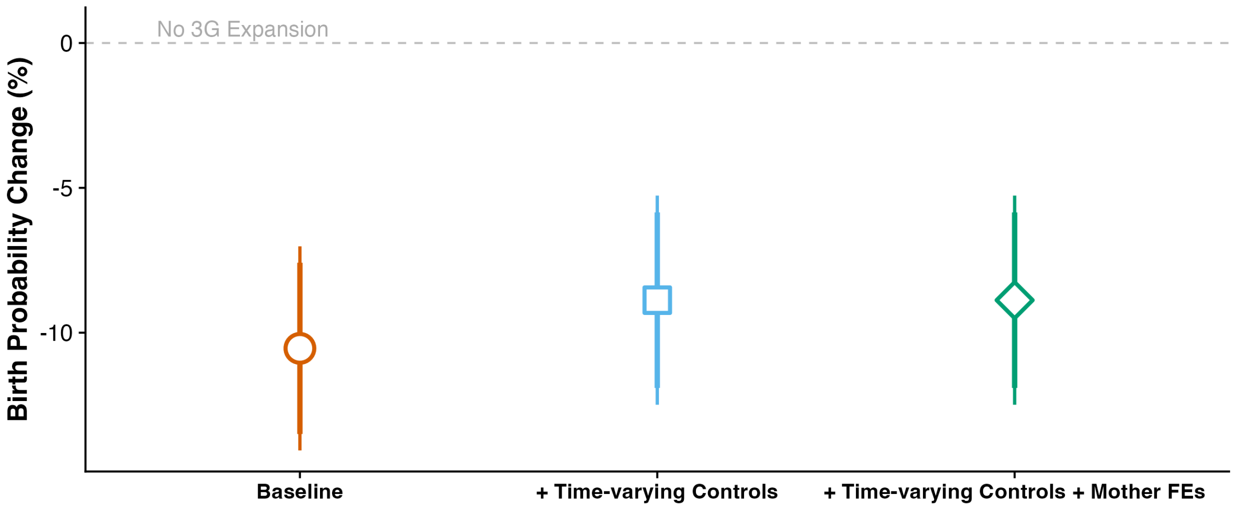

Figure 4: Relative change in probability of a birth. Estimated change in the probability of a birth in a given year, comparing models with and without individual-level controls. Estimates are shown for two 1: baseline models and models including time-varying cluster-level controls. Effects are presented as relative change evaluated at baseline.

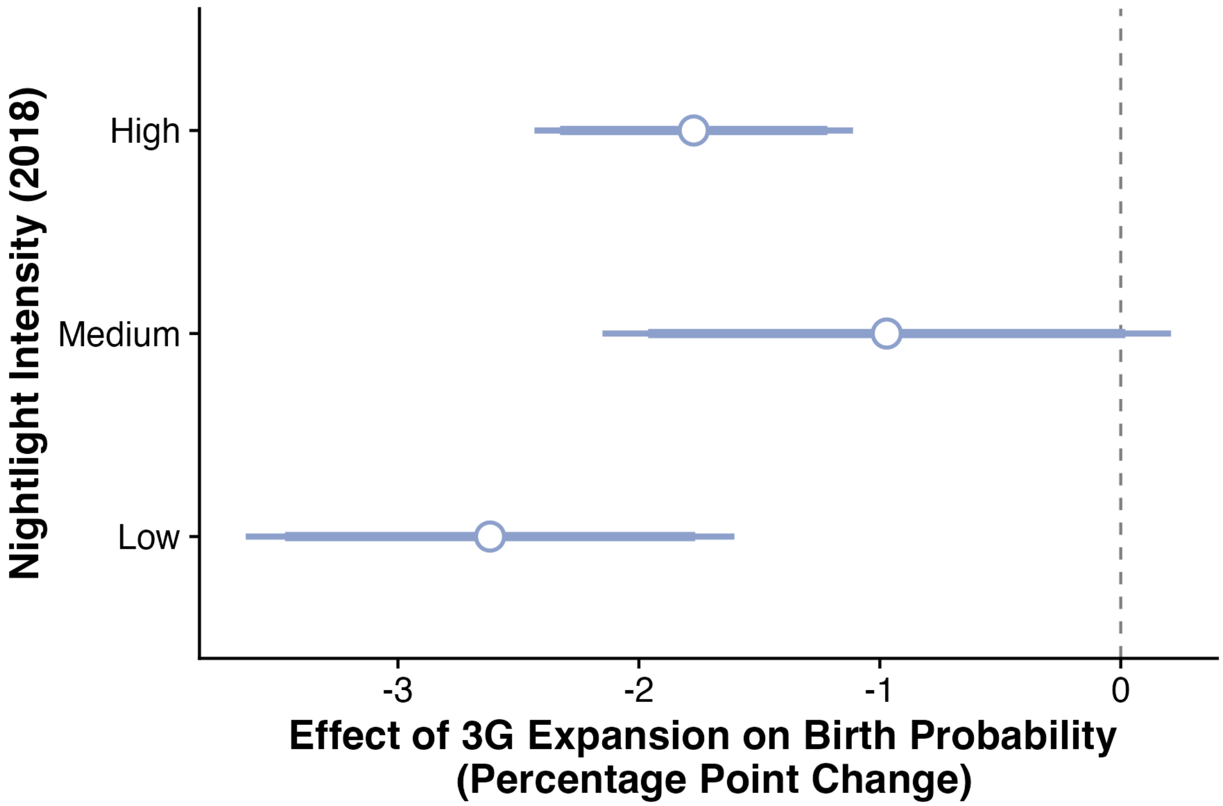

Figure 5: Effect heterogeneity by nightlight intensity, a common proxy for local development. Larger effects are observed in areas with lower nightlight levels.

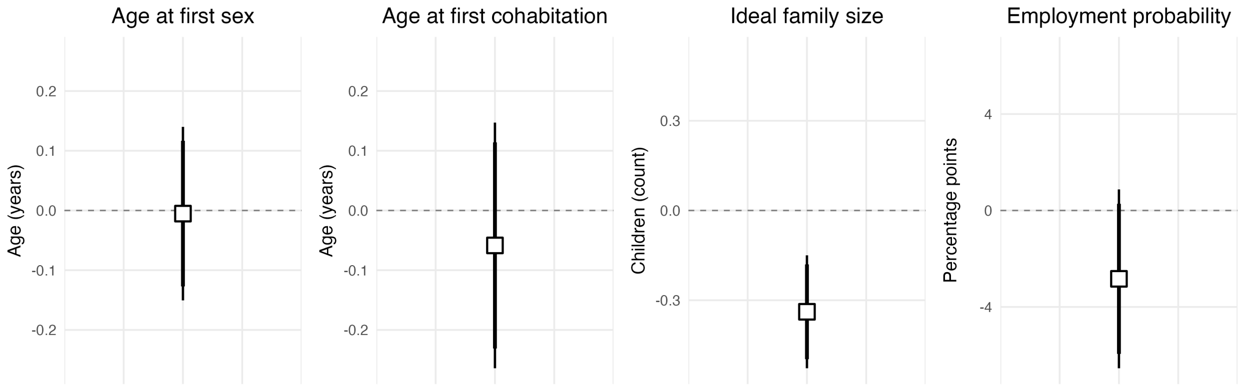

Figure 6: Association between 3G expansion and age at first cohabitation and ideal family size. Models include controls for wealth, education, Muslim religion, nightlights, meant temperature, GDP, and rainfall, with fixed effects for age and state.

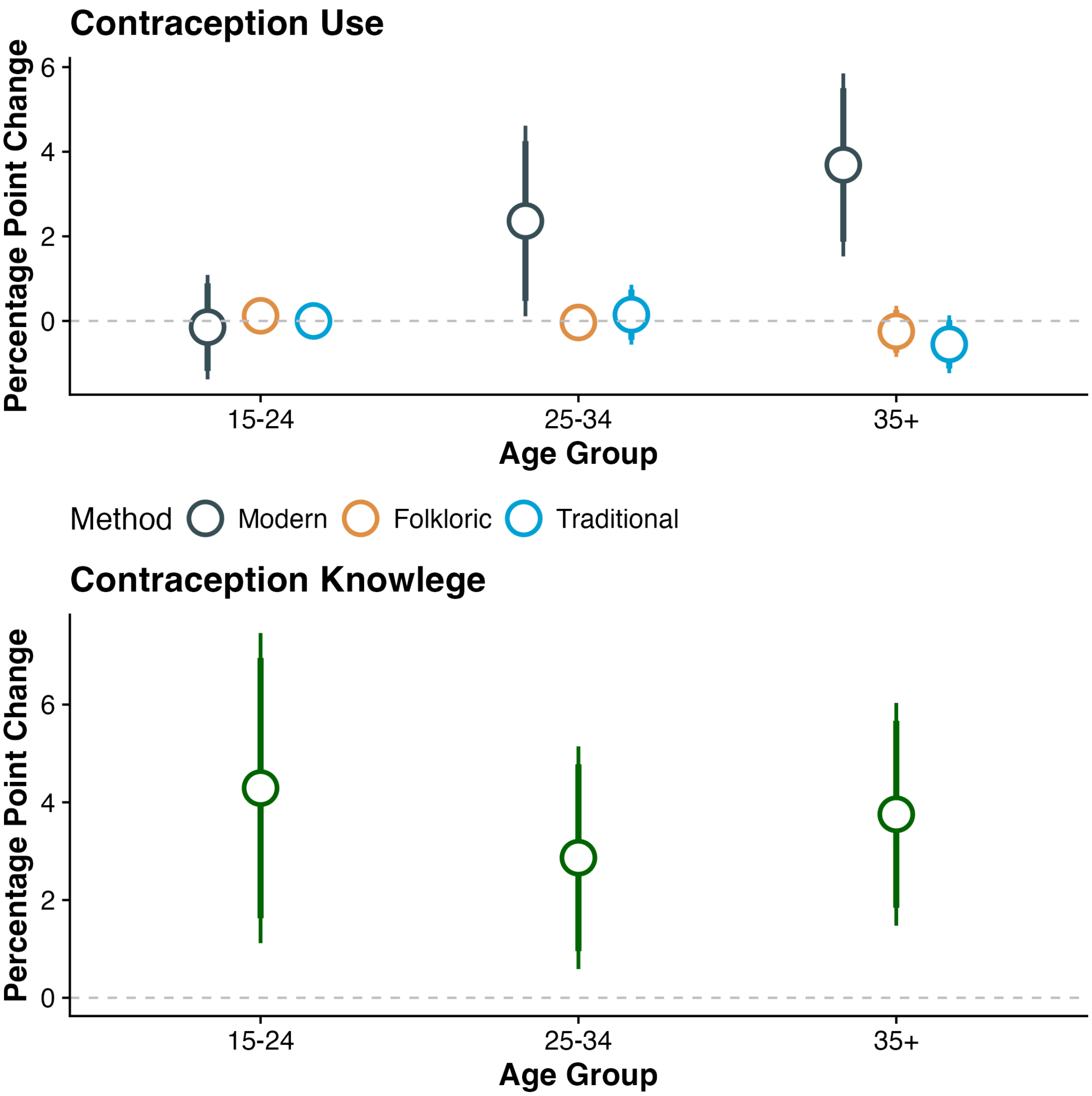

Figure 7: Association between 3G and contraception usage by age category.

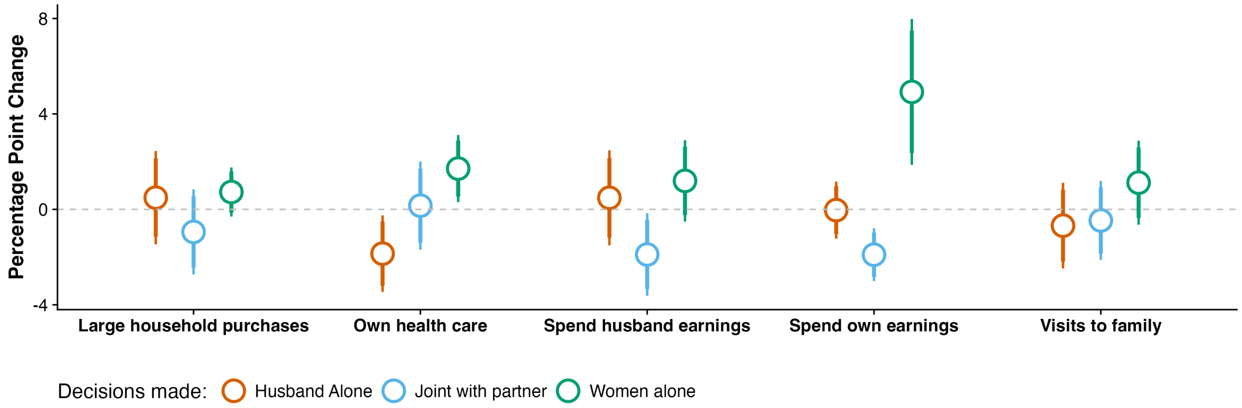

Figure 8: Change in likelihood of women making life decisions alone (red) or with partner (blue).

Online Appendix

The Fertility Impacts of 3G Mobile Expansion: Evidence from Nigeria

Casey F. Breen, Till Koebe, Ridhi Kashyap

A Processing Mobile Coverage Data

We use mobile coverage data provided by the GSMA, the global association of the mobile telecommunications industry, via their Connectivity Maps programme (GSMA-CM). The GSMA-CM data product was publicly available for 17 countries until March 2024, when GSMA discontinued public access to these data due to discontinuity of funding for the programme. We obtained these mobile coverage maps from the Mobile for Development (M4D) team of GSMA in June 2024 for academic research through a bilateral data agreement.

The maps are constructed from antenna-level technical specifications provided by a major Nigerian mobile network operator and processed into coverage maps by a technology consultancy on behalf of GSMA. Annual historic coverage maps were constructed based on the build dates of antennas. The native resolution of these maps is $30m \times 30m$ with estimated signal strength values for the technologies 2G, 3G, 4G and 5G at each pixel. The GSMA data we obtained is a 1% random sample of points with signal strength values binned into three different classes, namely *weak*, *moderate* and *strong*, for the technologies 2G, 3G and 4G, respectively (Figure A1).

The mobile coverage data used in this study should not be confused with another dataset provided by GSMA's mapping provider, Collins-Bartholomew (CB). While CB maps offer

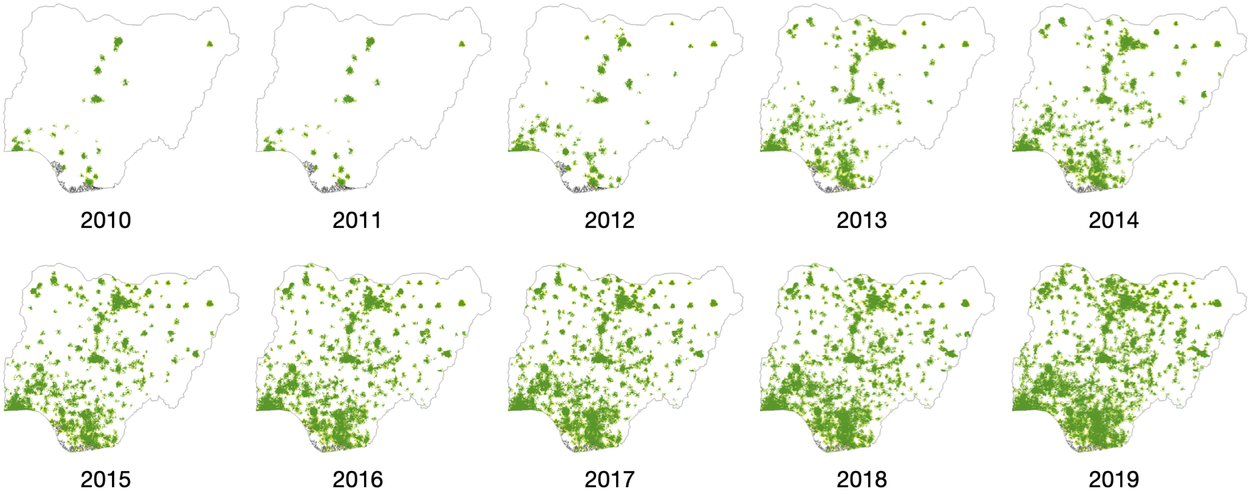

Figure A1: 3G coverage rollout in Nigeria, 2010–2019.

the most comprehensive spatial and temporal coverage, with data going back to 1999 and covering nearly every country at a 260 × 260 meter resolution, they have several shortcomings that need to be considered. First, major mobile network operators report to CB only infrequently, making it difficult to capture rollout dynamics consistently over time. Second, operators use different approaches to model the stochastic nature of radio signals, which hampers comparability. Consequently, comparisons across time and countries must be made with caution when using CB maps. In contrast, the GSMA maps used in this study, although limited in scope, are better suited for rollout modelling, because they are constructed using a consistent methodology. To exploit the complementary features of the two datasets (geographic scope and temporal consistency) and to allow for cross-country comparisons of our study results, we harmonize them in terms of geographical resolution and signal coding.

For our study, we align the GSMA maps with the CB maps in terms of resolution and signal strength classes for the reason of comparability. To do so, we allocate the sampled points from Nigeria to the CB grid of $260m \times 260m$ per pixel. Due to the higher native resolution of the GSMA data, a 1% sample in the GSMA map roughly corresponds to a

64% sample at CB resolution. After the points are allocated, we interpolate missing pixels considering the five nearest pixels with a maximum distance of 10km. We further align the different binning approaches in CB vs. GSMA by assigning the GSMA classes *weak* and *moderate* to the CB class *Variable*, while keeping the *strong/Strong* classes stable. Since we are interested in mobile broadband expansion (which can be delivered by 3G technology and above), we create a fourth layer of technology as the final preprocessing step by merging 3G maps and 4G maps into a single 3G+ map. These shares are calculated on a pixel-level by counting pixels classified as *strong* signal in the respective technology as 1 and 0 otherwise.

The survey data used in this study is collected via the Demographic Health Survey (DHS) program following a two-stage stratified cluster sampling design, using the 2006 Population and Housing Census of the Federal Republic of Nigeria (NPHC) as the sampling frame. Clusters are the primary sampling units in the 2018 Nigeria DHS and correspond to the enumeration areas of the 2006 NPHC. Clusters within each of the 74 strata used in this survey (36 Nigerian states + the Federal Capital Territory each divided into urban and rural areas) are selected using a probability proportional to size sampling scheme. After household lists were updated in all selected clusters, a fixed number of 30 households per cluster were selected for interview following an equal probability systematic sampling procedure. Interviewed households in the DHS are geolocated via the centroids of their respective clusters.

To better protect the privacy of the respondents, these centroids are displaced by up 2km in urban areas and up to 10km in rural areas. To account for this displacement, we draw a buffer with a radius equal to its maximum possible displacement around each cluster. This step ensures that it is almost certain that an interviewed household is located within the buffer area of the corresponding cluster. Since we are interested in narrowing down the coverage status of individuals living in a given DHS cluster, we clip the cluster buffers to sub-national boundaries as DHS surveys collected after 2009 do not displace cluster locations beyond their original admin-level 2 region. By overlaying the clipped buffers with the coverage maps and the high-resolution population maps, we generate four indicators per cluster–year: area and population coverage by 2G and by 3G+.

We then combine these data with the 2018 Nigeria DHS to create a longitudinal panel, as illustrated in Figure A2.

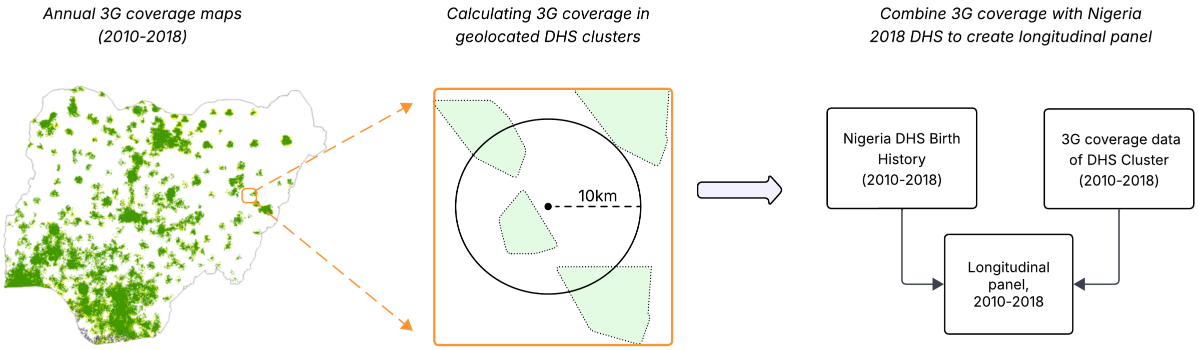

Figure A2: Illustration of longitudinal panel creation. We construct a woman-year panel by linking Nigeria's 2018 DHS to annual geospatial data on 3G mobile network coverage from 2010–2018. Left panel shows annual 3G coverage maps for the year 2018. We overlay maps with the DHS cluster locations. Center panel illustrates how we calculate 3G coverage: for each DHS cluster, we compute the population-weighted share of the buffer covered by 3G service in each year (2km buffer for urban, 10km buffer for rural). Right panel shows the resulting panel structure: each woman is observed across multiple years, with annual information on birth outcomes, 3G coverage, time-varying cluster level covariates (e.g., nighlights), and DHS covariates (assumed time-invariant).

B Robustness checks

As a robustness check, we replicate our analysis using a separate identification strategy. Specifically, we use both the 2008 and 2018 Nigeria DHS surveys and exploit plausibly exogenous rollout between surveys. In 2008, the year of our first DHS survey, no DHS cluster in our sample had 3G coverage. In the 2018, 39.5% of DHS clusters in our sample had 3G coverage.

For identification, we use a difference-in-differences (DiD) model. The model takes the form:

$$B_{ict} = \beta_0 \quad + \quad \underbrace{\beta_1 \left(3\mathrm{G}_c \times \mathrm{Post}_t\right)}_{\text{DiD Interaction Term}} \quad + \quad \underbrace{\gamma_c + \delta_t}_{\text{Cluster and Year FE}} \quad + \quad \underbrace{\beta \mathbf{X}_i}_{\text{Individual and cluster controls}} \quad + \quad \epsilon_{ict} \qquad (3)$$

where B_{ict} is an indicator for whether woman i in cluster c at time t had a birth in the past year,[6] $3\mathrm{G}_c \times \mathrm{Post}_t$ is the interaction of the proportion of the cluster c with 3G coverage interacted with whether or not the pre- or post-period, γ_c represents pseudo-cluster fixed effects, δ_t represents time fixed effects, and $\beta \mathbf{X}_i$ represents a set of individual- and cluster-level control variables.

This difference-in-differences model compares the change in birth probability over time between clusters that gained 3G coverage and those that did not, across the period from 2008 to 2018. The intuition behind this approach is that the rollout of 3G networks is plausibly exogenous within clusters. By interacting the 3G coverage variable with the post-treatment period, the model captures the differential effect of 3G expansion on birth rates, isolating the impact of 3G from time-invariant factors and common temporal trends.

We include a series of control variables in our model. First, we include individual-

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[6] We also use births in the last five years as the outcome of interest to increase statistical power. However, the disadvantage of using a longer retrospective fertility window is that we cannot definitively determine which of those five years had 3G coverage using our coverage maps.

level controls for household wealth, urban/rural, age, employment status, education, and religion to account for sociodemographic differences that may influence both exposure to 3G coverage and fertility. Second, we include a series of cluster-level controls for GDP, nightlights, temperature, and rainfall. In addition, we adjust for the population share of each cluster covered by 2G mobile coverage to more clearly identify the effect of 3G internet. Finally, we include the pseudo-cluster and year fixed effects to control for time-invariant cluster characteristics and any time trend between 2008 and 2018.

The results are shown in Figure A3. We find a effect of an approximately 4-8% decline, which is in agreement with our estimate from our main specification.

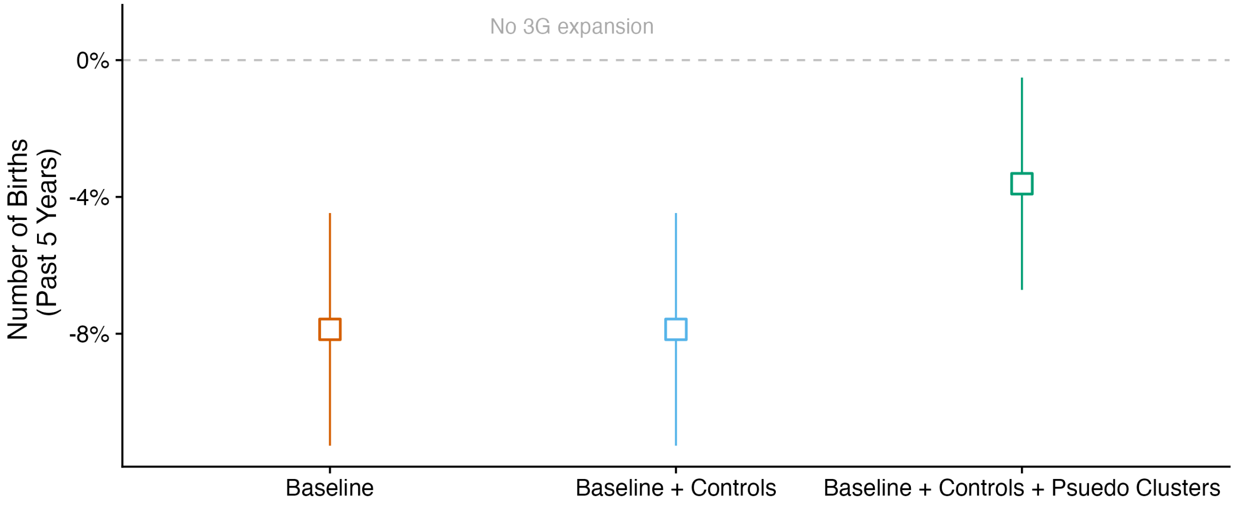

Figure A3: Causal effect of 3G expansion on fertility using an alternative identification strategy.

B.1 Event Study

As an additional robustness check, we re-estimate effects using the Sun and Abraham estimator (Sun and Abraham, 2021). The main advantage of this alternative estimator is that it provides consistent estimates even in the presence of heterogeneous treatment effects. Our results remain substantively unchanged, which increases confidence in the robustness of our findings. In particular, we find little evidence of pre-trends, suggesting that fertility was not differentially declining in clusters that adopted 3G coverage. The absence of pre-trends strengthens the causal interpretation of our TWFE estimates.

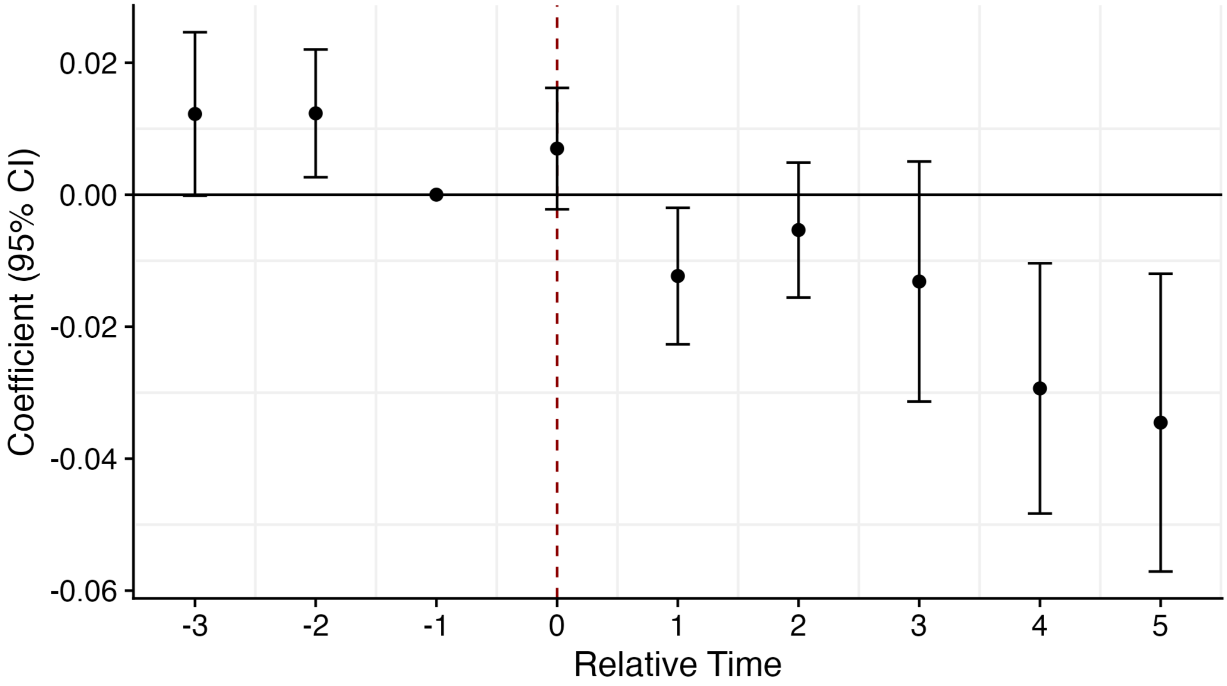

Figure A4: Estimates from an event study using Sun and Abraham estimator.

C 3G Effects on Infant Mortality

Here, we present results on the effects of 3G expansion on infant mortality. We fit an adapted version of the model in Equation 2, with the outcome defined as whether an infant under 12 months died in the past year. Compared to fertility, child death is a rare event, leaving the analysis underpowered to detect small effects. Without controls, full 3G expansion corresponds to roughly a 2% decline in infant mortality. However, in models with fixed effects and controls, we find no statistically significant effect.

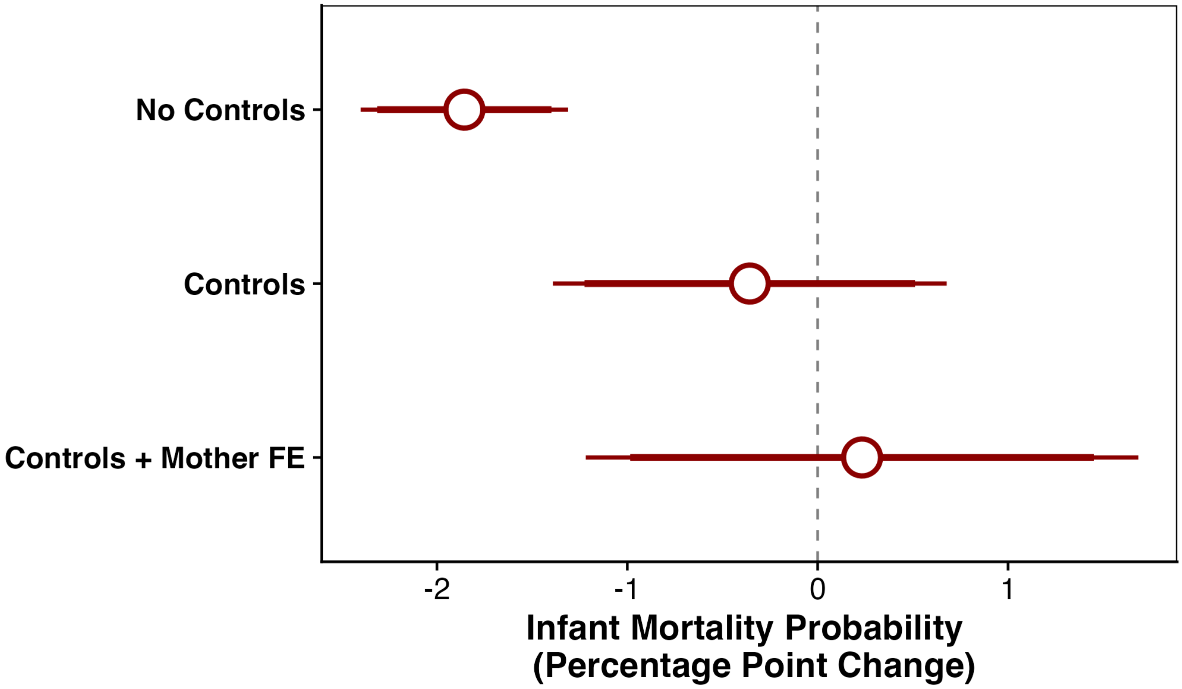

Figure A5: Effect of 3G expansion on in the probability of infant mortality.

D Effect heterogeneity

We examine heterogeneity along three key dimensions: phone ownership, marital context, and geography. As shown in Figure A6, effects are concentrated among women who owned a mobile phone, with no detectable impact among non-owners, suggesting that individual access is the primary channel rather than household or community spillovers. In Figure A7, we find large negative effects among women in monogamous unions but no effect among those in polygynous unions or among unmarried women, consistent with the centrality of union type in shaping fertility behavior. Finally, as shown in Figure A8, we observe no substantial differences between the North and South, indicating that regional disparities in fertility and development do not translate into heterogeneous effects of 3G expansion.

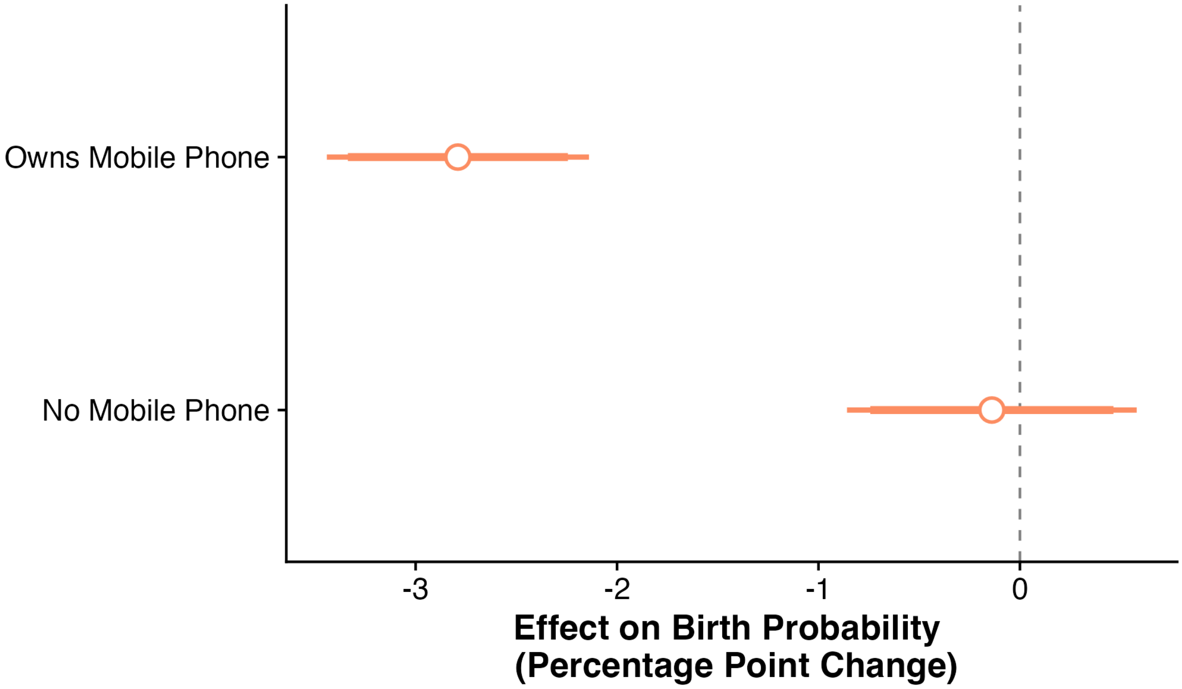

Figure A6: Heterogeneous effects by mobile phone ownership status

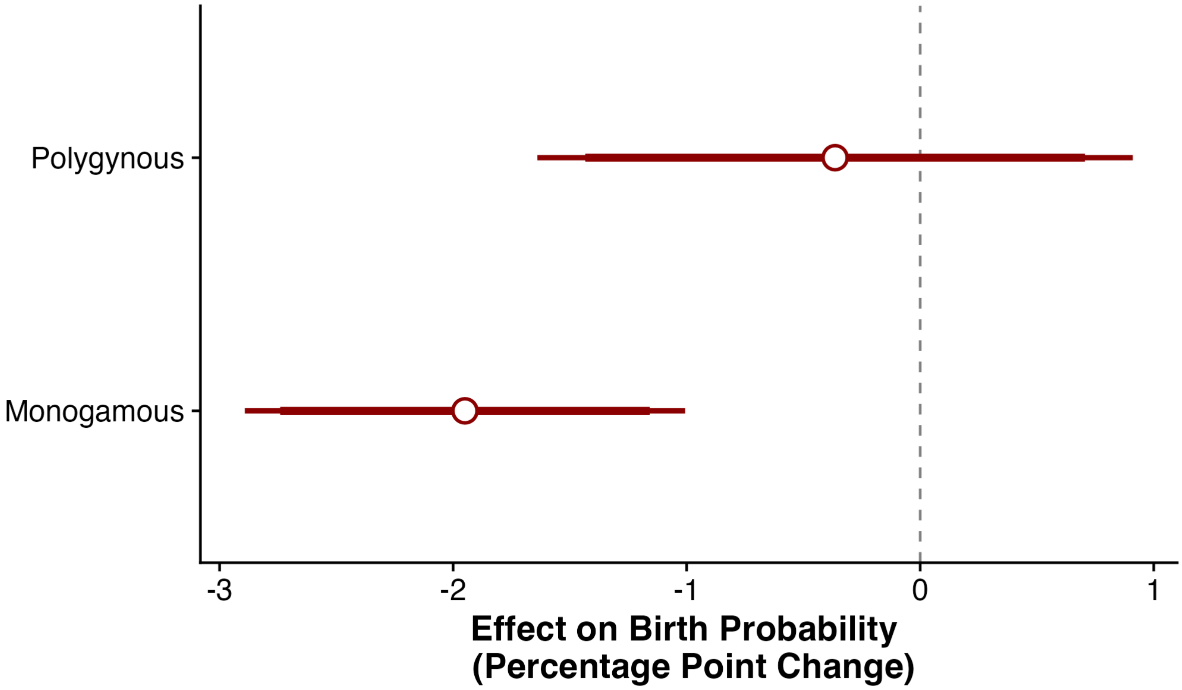

Figure A7: Heterogeneous effects by polygynous unions vs. monogamous unions.

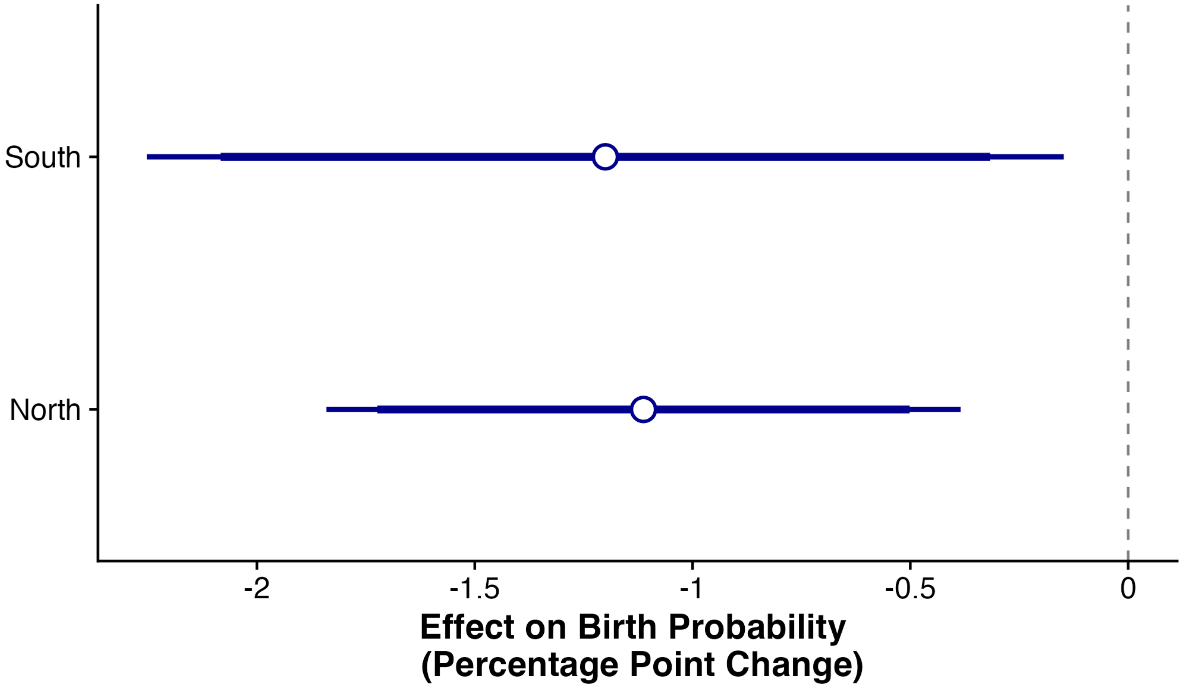

Figure A8: Heterogeneous effects by geography. North covers the regions of North Central, North East, North West, while South covers South East, South South, South West.

E Full regression tables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.187*** (0.002)					
% Pop. Covered by 3G (lag 1y)	-0.057*** (0.004)	-0.018*** (0.003)	-0.018*** (0.003)	-0.015*** (0.003)	-0.015*** (0.003)	-0.0145*** (0.00)
% Pop. Covered by 2G (lag 1y)		0.000 (0.007)	0.000 (0.007)	0.002 (0.007)	0.002 (0.007)	0.005 (0.008)
Prior Children (pre-window)		0.016*** (0.001)	0.015*** (0.001)	0.016*** (0.001)	0.015*** (0.001)	
Wealth Index			-0.001 (0.001)		-0.001 (0.001)	
Working			0.002 (0.002)		0.002 (0.002)	
Education			-0.020*** (0.002)		-0.020*** (0.002)	
Muslim			0.023*** (0.005)		0.023*** (0.005)	
Watches TV Freq.			-0.004** (0.002)		-0.004** (0.002)	
Listens to radio Freq.			-0.003* (0.002)		-0.003* (0.002)	
Night Lights per Capita (Cluster-year Level)				0.001* (0.000)	0.001$^+$ (0.000)	0.001 (0.001)
GDP per Capita (Cluster-year Level)				0.000 (0.000)	0.000 (0.000)	0.000* (0.000)
Mean Temperature (Cluster-year Level)				-0.022*** (0.005)	-0.022*** (0.005)	-0.051*** (0.007)
Mean Rainfall (Cluster-year Level)				0.011** (0.004)	0.011** (0.004)	0.026*** (0.004)
FE: Year		X	X	X	X	X
FE: 2010/2011 Birth × Year		X	X	X	X	X
FE: Birth Cohort		X	X	X	X	
FE: Cluster		X	X	X	X	
FE: Mother						X
Observations (Person-years)	223,915	223,915	223,915	223,915	223,915	223,915
R^2	0.003	0.124	0.126	0.124	0.126	0.302
Adj. R^2	0.003	0.120	0.122	0.120	0.122	0.214
Within R^2		0.033	0.035	0.033	0.035	0.143
Adj. Within R^2		0.033	0.035	0.033	0.035	0.143
AIC	199,130.8	172,140.4	171,731.6	172,116.1	171,706.6	169,272.1
BIC	199,151.4	182,438.8	182,091.9	182,455.7	182,108.1	427,072.2
RMSE	0.38	0.35	0.35	0.35	0.35	0.32
Std.Errors	by: Cluster	by: Cluster	by: Cluster	by: Cluster	by: Cluster	by: Cluster

Significance levels: $^\dagger p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table A1: Results from linear probability models predicting the likelihood of a birth in a given year. The outcome is a binary indicator for whether a woman had a birth in year t. All coefficients are reported as marginal effects. The baseline probability of a birth across all women and years is 17%. The sample includes women observed from 2010 to 2018 and is restricted to clusters that had no 3G coverage at baseline in 2010. Coefficients can be interpreted directly as percentage point changes in probability of birth in a given year.

	Age at First Cohabitation	Ideal Family Size	Employment Probability
3G Expansion	-0.059	-0.339***	-0.043*
	(0.105)	(0.096)	(0.017)
Wealth Index (1–5)	0.162***	-0.129***	-0.005
	(0.039)	(0.025)	(0.005)
Education Level (0–3)	0.654***	-0.369***	0.005
	(0.049)	(0.028)	(0.005)
Currently Working	-0.329***	0.285***	
	(0.074)	(0.062)	
Muslim	-0.868***	1.096***	-0.077***
	(0.117)	(0.104)	(0.018)
Radio Frequency (0–2)	-0.023	0.074**	0.046***
	(0.050)	(0.028)	(0.005)
TV Frequency (0–2)	0.106*	-0.168***	-0.010+
	(0.054)	(0.031)	(0.006)
Road Density (km)	0.006	0.004	0.001
	(0.005)	(0.004)	(0.001)
Night Lights (mean)	0.054**	-0.029+	-0.003
	(0.019)	(0.017)	(0.003)
Mean Temperature	-0.047	0.019	0.005
	(0.036)	(0.033)	(0.010)
GDP (weighted)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Mean Rainfall	-0.035	-0.088	0.011
	(0.066)	(0.054)	(0.008)
Fixed Effects: Age	Yes	Yes	Yes
Fixed Effects: State	Yes	Yes	Yes
Observations	7,069	30,541	31,444
R^2	0.728	0.344	0.212
Adj. R^2	0.725	0.342	0.210
Within R^2	0.096	0.063	0.010
Adj. Within R^2	0.095	0.062	0.010
AIC	32,268.9	140,729.3	35,715.5
BIC	32,831.7	141,420.4	36,400.6
RMSE	2.34	2.42	0.43
Std. Errors	clustered by PSU	clustered by PSU	clustered by PSU

Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table A2: Association between 3G expansion and age at first cohabitation and ideal family size.